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Comparative Study on Supply Chain Complexity Management Efficiency of Global Automobile Companies

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ABSTRACT

Comparative Study on Supply Chain Complexity Management Efficiency of Global Automobile Companies

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Complexity Management has recently attained considerable attention from both academia and practice. Especially, multinational companies with global supply chains are suffering from this complexity crisis as the business environment gets more complicated. Although it seems evident that complexity will harm the performance of the supply chain, there has been little scientific research conducted on this topic.

In this study, I focused on the managerial efficiency of supply chain complexity in global automotive industry. Then a model based on Data Envelopment Analysis (DEA) was adopted in order to evaluate the relative efficiency of supply chain complexity management.

First of all, input variables and output variables were selected from an extensive literature review of preceding research. Factors such as numbers of product types, business divisions, and production facilities of each company were collected as input measures, and net profit was selected as an output measure. Then the initial model was designed with these variables. Secondly, a total of 20 global car manufacturers were selected as decision making units of the model. After the initial analysis, an alternative model with 15 decision making units was designed to achieve a better result reflecting the actual automobile market conditions.

The results of the study are summarized as follows: Toyota and B.M.W. both showed the highest efficiency value (1.0000), following Hyundai Motors (0.8398), Daimler AG (0.7990), and GM (0.7679). In contrast, Fiat-Crysler (FCA) showed the lowest efficiency score (0.061) following Peugeot-Citroen PSA Group (0.1737), Mitsubishi Motors (0.1746), and Suzuki Motors (0.2656).

The study contributes to further understanding of the supply chain complexity by measuring relative efficiency score of each unit. Also, practitioners in the industry could find a room for improvement by benchmarking the results of the study.

Keywords: **Supply Chain Complexity; Data Envelopment Analysis; Global Automobile Companies**

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I. INTRODUCTION

Today, many companies in the global supply chain are suffering from complexity crisis. As the global business environment continually becomes more complicated, supply chains are in turn becoming more complex than ever. To this end, supply chain complexity has become an important subject for researchers and practitioners in the field of supply chain management.

According to IBM's 2010 Global CEO Study, which conducted 1,500 face-to-face interviews with CEOs from companies across 60 countries and 33 industries, most of the top executives answered rapidly changing the business environment as their most challenging issue. In other words, about 79% of total respondents pointed out that the increased uncertainty and complexity in operating their business is becoming their primary challenge.

Also, Samjong KPMG Economic Research Institute conducted another global study on complexity management in 2011. Again, more than 1,400 CEOs and CFOs answered complexity management as the most significant issue in current business environment. They said that companies which efficiently manage the business complexity would eventually succeed in this turbulent era. In this paper, I mainly focused on the supply chain complexity, rather than a more general concept of management complexity.

Various definitions of supply chain complexity have been suggested by preceding researchers. Wilding (1998) proposes a concept called supply chain complexity triangle, but it was too ambiguous to be treated in scholarly research. Vachon and Klassen (2002) attempt to provide a multi-dimensional definition of supply chain complexity with an empirical analysis to link the concept to delivery performance. On the other hand, Choi et al. (2001) propose a different definition of supply chain complexity, using the idea of “complex adaptive system” which is widely studied in systems science literature.

Exploring the factors that drive the complexity level of the supply chain is also significant. Bozarth et al. (2009) and Serdarasan (2013) have summarized various drivers of supply chain complexity. However, little scientific research has been conducted on this subject. Therefore, researchers are trying to investigate more insights from the supply chain complexity.

Kim & Kim (2015) designed a Data Envelopment Analysis (DEA) model to compare the relative efficiency of supply chain complexity of 12 Korean companies. They showed that the number of goods, the number of connected companies, and the number of plants and branches affect the managerial complexity of supply chain and proposed benchmarking points for each firm by analyzing projection points and excess quantity of inputs of each decision making unit.

The purpose of this paper is to extend Kim & Kim (2015)'s attempt to study the supply chain complexity of the global automobile industry. Unlike Kim & Kim (2015), which chose sample decision making units from a range of different sectors, I considered global vehicle makers as the target group of the study in order to improve the clarity of the analysis.

Major global automakers have experienced a lot of changes from past decades. After the global economic crisis in 2008, major car manufacturers in the United States like Ford and General Motors had suffered a severe downturn. Then Toyota took their place after the crisis stroke the market. However, Toyota also encountered a massive recall crisis and lost their dominance in the global automobile industry for several years.

Volkswagen's recent diesel-gate scandal also has shocked the automobile market as well. On September 2015, U.S. Environmental Protection Agency (EPA) revealed that Volkswagen had intentionally programmed the engine system of its vehicle to meet the environmental standards of nitrogen oxide emissions. More surprisingly, this illegal programming was applied to more than 10,000,000 vehicles worldwide. After the news had released, Volkswagen's stock price decreased more than 30%, and the company lost its market position in the automobile market.

Another huge change in the industry has been occurring in China. Since 2010, China's motor vehicle production ranks the top in the global automobile market. According to the 2014 World Motor Vehicle Production Report, Chinese automakers, such as SAIC (ranked 13^{th}), Changan (ranked 15^{th}), Dongfeng (ranked 17^{th}), and BAIC (ranked 19^{th}) and other companies, are changing the dynamics of global automobile industry.

These dynamic changes in the automobile market make the supply chain more complex. Therefore, I captured this apparent need for academic research on complexity management. To construct the input and output factors for conducting a Data Envelopment Analysis (DEA), I collected data on the numbers of business divisions, manufacturing plants, and product types and others for 20 global automakers from each company's annual report and official website. Then I compared the relative efficiency of supply chain complexity of each company by using an input-oriented DEA model developed by Charnes et al. (1978)

Contrary to Kim & Kim (2015), this research aims to focus on a single industry to improve the chances of actual application in real business practice. Besides, the study contributes to the literature of supply chain management by presenting new ideas of constructing the variables. Lastly, this study proposes a model which could be used to evaluate the efficiency of supply chain complexity management.

The paper is structured as follows. In the following section, an extensive literature review on supply chain complexity and automobile industry is suggested. It is followed by a section that explains the research methodology, including the details of the constructs and decision making units. Then the results of the DEA are summarized with comments and discussions. Lastly, future research opportunities are suggested in the last section of the paper.

II. LITERATURE REVIEW

This chapter reviews previous academic research on Supply Chain Management Complexity as well as several articles that studied recent issues on the automotive industry in the perspective of supply chain and operations management. By reviewing prior studies, the gap which instigated this study could be identified and potential research ideas would be suggested as well.

2.1. Supply Chains in Automotive Industry

From Henry Ford Company's conveyor-belt assembly system to Toyota's lean production, automotive industry has always been an important subject of study in operations and supply chain management. However, only a selected articles which have influenced this study will be discussed in this chapter.

Marcus Brandenburg (2016) suggests an empirical model to evaluate the impacts of supply chain efficiency on corporate value. He used a secondary database named AMADEUS to analyze the European automotive industry in the years 2002–2010. Although the research methodology is different, his attempt to empirically test the supply chain performance through secondary data has affected this study.

Thomé et al. (2014) show the effects of supply chain flexibility by multi-tier supply chain analysis. They explored supply chains of Brazilian automobile companies and figured out that constraints such as suppliers´ capacity, diversity of suppliers, suppliers´ cooperation, tariffs, exchange rates and inventory levels were identified as the main factors influencing the supply chain flexibility. Their approach toward supply chain flexibility helped the understanding of supply chain complexity.

Thun and Hoenig (2011) studied German automotive industry to analyze the relationship between supply chain risk management and firm performance. They surveyed 67 manufacturing plants to examine the vulnerability of supply chains and extract factors that may increase supply chain risk. As a higher level of supply chain complexity would in turn eventually lead to greater supply chain risks, understanding the drivers of supply chain risks was important to construct the measures of the model of this paper.

Sánchez & Pérez (2005) published an interesting article on the relationship between supply chain flexibility and firm performance. They designed a multivariate model then empirically tested their model by using a survey data with a sample of 126 Spanish automotive suppliers. The result of their study indicates that there is a positive correlation between supply chain flexibility capabilities and firm performance.

2.2. DEA in Automobile industry

Many articles have adopted DEA to analyze the productivity and efficiency of the companies in automotive industry. However, these previous attempts have certain limitations on narrow scope of the study. Most of the existing studies are focusing a market or industry in a single country, therefore, the results of them might not be smoothly applied to a generalized setting in the perspective of a global market.

For example, Dang-Thanh, N., & Tran, D. H. (2014) used DEA to evaluate the performance of the Vietnamese Automobile Company, and Gonzalez et al. (2013) tried to evaluate product efficiency in the Spanish automobile market by using nonparametric DEA techniques. Additionally, Nandy (2011) studied Indian automobile market which has been growing at a rapid pace in the global automotive industry. Also, Bai & Dai (2006) analyzed the production efficiency of leading car manufacturers in China using a conceptual model based on DEA.

Although there are a variety of existing articles that used DEA to study automobile industry, most of them used DEA to analyze the productivity efficiency of each company, not in a supply chain context. Therefore, the aim of this paper to measure the efficiency of supply chain complexity management could be an interesting approach to have a better understanding of the automotive supply chain.

2.3. Managing Complexity

With the advancement of technology, most business activities are not limited by the geographical boundary anymore. Darrel Rigby (2010) classified the management complexity into three categories: product complexity, process complexity, and organizational complexity. Wilson & Perumal (2009) then suggested a conceptual framework called "Complexity Cube" to emphasize the importance of concurrent management of all three factors of complexity. Mariotti (2007) also warned the risk of failure to manage the managerial complexity. He proposed "Complexity Index" to evaluate the level of complexity of each company.

In the perspective of global supply chain, managing complexity is more important than ever and companies are discovering more business opportunities from international sales and production reshoring. As a result, both buyers and suppliers in the supply chain network have to increase their level of complexity to meet the various demands of global markets. To this end, more type of products require more type of components and eventually lead to an increase in process complexity.

Inman & Blumenfeld (2014) suggest that product complexity has a negative effect on supply chain performance. They assumed that a complex product having a broad range of product components would bring the supply chain at risk. Therefore, manufacturers with a complicated process are vulnerable to supply chain risk. Berglund et al. (2013) studied the impact of complexity from mass customization. They mainly focused on the relationship between complexity, quality, and cognitive automation. Their result shows that complexity has a positive correlation with assembly error, and proposed that cognitive automation can relieve the negative effect of complexity. Hu et al. (2008) also point out that complex supply chain process may harm supply chain performance by more human errors and increased inventory level. Additionally, Milgate (2001) concludes that complicated supply chain systems may have an adverse impact on delivery performance.

2.4. Drivers of Supply Chain Complexity

It is evident that complexity has a negative impact on overall supply chain performance. However, little research has been done on exploring the drivers of supply chain complexity. Serdarasan (2013) tried to reveal those drivers by conducting extensive literature reviews. Bozarth et al. (2009) also made a contribution to classification of the drivers of supply chain complexity. They categorized the drivers in three levels (Downstream, Internal, and Upstream) and then conducted an empirical study to verify their conceptual model. Based on the previous literature, main drivers of supply chain complexity can be summarized as Table 1 below.

<Table 1: Main Drivers of Supply Chain Complexity>

Factors (Variables)	References
Number of Suppliers	Choi et al., 2001; Goffin et al., 2006; Mariotti, 2007; Serdarasan 2013
Supplier Distribution	Bozarth et al., 2009; Wilson and Perumal, 2009
Number of Products (or Product Models)	Ashkenas, 2007; Bozarth et al., 2009; Mariotti, 2007; Wilson and Perumal, 2009; Closs et al., 2008; Salvador et al., 2002; Serdarasan 2013;
Number of Parts (or Components)	Fisher et al., 1999; Krishnan and Gupta, 2001; Wilson and Perumal, 2009
Number of Production Plants	Mariotti, 2007
Number of Business Divisions	Kim and Kim 2015
Number of Processes	Ashkenas, 2007; Serdarasan, 2013;
Number of Customers	Mariotti, 2007; Wilson and Perumal, 2009; Serdarasan 2013;
Number of Affiliates and Subsidiaries	Kim and Kim 2015
Number of Brands	Wilson and Perumal, 2009

III. METHODOLOGY

3.1. Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a mathematical approach to measure relative efficiency of entities in a certain group. These entities are called decision making units (DMUs) which have multiple input and output variables. As one of the major productivity analysis models, DEA has been widely used in various fields as a nonparametric methodology with several advantages.

First, DEA does not require strict assumptions about the relationships between input and output variables. Second, DEA is applicable to various settings without manipulating the data. According to ISI Web of Science database, more than 4,500 publications using DEA have been published until 2010. (Liu et al. 2013)

Basic DEA model was developed by Charnes et al. (1978) as a linear programming problem to maximize the efficiency ratio which is calculated by the weighted sum of input values and output values. Also, the maximum efficiency ratios are constrained to one, and the weights of each input and output variables should be above zero. The formula and given conditions can be mathematically represented as follows.

$$\text{Maximize } \theta_0 = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \text{ (Efficiency Score)}$$

$$\text{s.t. } \theta_0 \leq 1,\ u_r \geq 0,\ v_i \geq 0 \ for\ all\ r\ and\ i$$

y_{rj} = Quantity of rth output of jth DMU, x_{ij} = Quantity of ith input of jth DMU

j…n=Number of DMUs, r…s=Number of Outputs, i…m= Number of Inputs

u_r = Weight of rth Output, v_i = Weight of ith Input

Since Charnes-Cooper-Rhodes (CCR) suggested the basic DEA model, many researchers tried to advance the methodology by adding some variations to the original model. Banker et al. (1984) is one of the breakthroughs in DEA's development. They proposed a model which covers returns-to-scale assumption to consider the scale of DMUs. Latest DEA models are extending its boundaries to two-stage DEA (Simar 2007; Banker 2008), network DEA (Yu and Lin 2008; Cook et al. 2010), dynamic DEA (Chen 2009; Tone 2010) and bootstrapping DEA models (Simar 1999; Simar 2000).

Also, many researchers in the field are trying to relax the constraints of the model. DEA models assume the data to be positive numeric values. However, real life data can include negative values, bounded limits, and ordinal values. Cooper et al. (2004) is one of the outstanding guidelines to review recent developments of DEA models. In this study, however, the basic input-oriented DEA-CCR model which presumes constant returns to scale was used to simplify the model.

3.2. Input and Output Variables

Based on the literature review, five input variables and two output variables were initially selected through a series of consideration process. In the first step, variables such as process uncertainty, market uncertainty, customer heterogeneity, and demand variability were carefully excluded as it is very difficult to collect relevant data to quantify those variables. Second, variables such as the number of parts (components), the number of customers, the number of suppliers, and the number of processes were also ruled out although they seem to have a significant impact on supply chain complexity. Even though these variables are objectively measurable, it was impossible to collect the data because these figures are mostly confidential to the company.

Finally, a total of five input variables and two output variables were selected to construct a preliminary model. The availability of data was an important criterion to select the input variables. Especially, the figures that are open to public through the annual report and official website were chosen as input variables: Number of Business Divisions, Number of Brands, Number of Product Models, Number of Production Plants or Facilities, and Number of Product Types. Also, two output variables – Revenue and Net Profit – were retrieved through financial databases and annual reports.

3.3. Decision Making Units

A total of 20 global automakers were selected from the 2014 world vehicle production report. As Banker et al. (1984) suggest the optimal number of DMUs should be three times bigger than the total number of both input and output variables, some of the variables must be eliminated, or more DMUs must be added before conducting further analysis. After conducting a correlation analysis between variables, sales data was eliminated then net profit was used as a single output variable because two output variables showed a correlation of 0.851. The complete list of decision making units is summarized below.

<Table 2: List of Decision Making Units>

Rank	DMU (Decision Making Unit)	Production (Units)	Net Profit (Million Dollars)
1	TOYOTA	10,475,338	18231.2
2	VOLKSWAGEN	9,894,891	12174.8
3	G.M.	9,609,326	3500.0
4	HYUNDAI MOTORS	8,008,987	7436.8
5	FORD	5,969,541	3187.0
6	NISSAN	5,097,772	4575.7
7	FCA (FIAT CRYSLER)	4,865,758	695.2
8	HONDA	4,513,769	5094.0
9	SUZUKI	3,016,710	968.6
10	PSA	2,917,046	995.5
11	RENAULT	2,761,969	2079.0
12	B.M.W.	2,165,566	6398.7
13	SAIC	2,087,949	5730.0
14	DAIMLER AG (BENZ)	1,973,270	8019.0
15	CHANGAN	1,447,017	1091.9
16	MAZDA	1,328,426	1588.0
17	DONGFENG (DFMG)	1,301,695	2094.0
18	MITSUBISHI MOTORS	1,262,342	1182.0
19	BAIC GROUP	1,115,847	876.2
20	TATA MOTORS	945,113	2083.0

IV. RESULTS

Table 3 in appendix section describes the results of preliminary DEA model with five inputs, one output, and 20 DMUs. A brief overview of the table and then a detailed explanation of the results are summarized. First, the most efficient decision making units with the highest efficiency score are Toyota, Volkswagen, B.M.W, and SAIC. In contrast, the least efficient DMU is FCA (Fiat Crysler Automobiles) with an efficiency score of 0.058.

Second, according to the data, the supply chain of Volkswagen seems complicated, having 355 product models and 199 production plants, each of which is far above the average. However, Volkswagen's efficiency ranked the highest because of the tremendous net profit of the company in the 2014 fiscal year, which might be explained by the Diesel-Gate scandal. Therefore, an alternative model without Volkswagen data should be constructed and analyzed in order to achieve more reliable results.

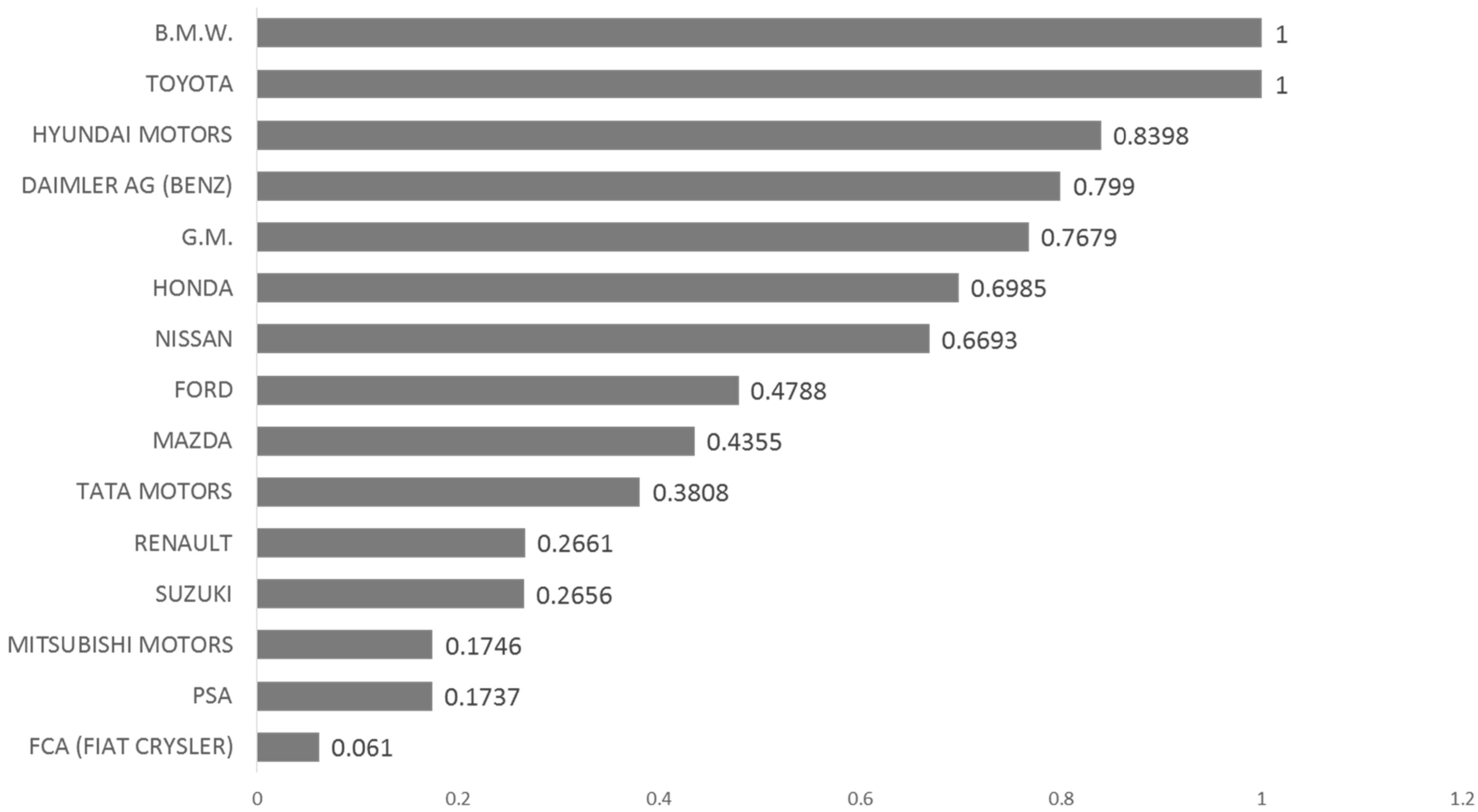
Third, the reliability of the data of Chinese automakers could be questioned. As most of the Chinese automakers operate a joint venture with other global manufacturers, like Shanghai-GM, Shanghai-VW, Changan-Suzuki, and Changan-Ford, their financial figures would distort the results of the DEA model.

For these reasons, an alternative DEA model with 15 DMUs after eliminating four Chinese automakers (SAIC, Changan, Dongfeng, and BAIC) and Volkswagen should be constructed. Then, a model with higher validity which better explains the actual automobile industry would be accepted.

Table 4 in appendix then shows the results of alternative DEA model with five inputs, one output, and 15 DMUs. After removing five DMUs, the model shows more reasonable results. First, both Toyota and B.M.W. now become the most efficient DMUs with the highest scores (1.0000), which is a result better explains the dominance of the actual global automobile market. Then, in contrast, FCA (0.061), PSA (0.1737), Mitsubishi (0.1746), and Suzuki (0.2656) were identified as inefficient decision making units.

Figure 1 and Figure 2 both show the efficiency scores of each DMU. The first figure is ordered by efficiency scores which intuitively describes the overall supply chain management efficiency of the global automobile industry. Clearly, Toyota, B.M.W., and Hyundai Motors performs better at managing supply chain complexity than FCA, PSA, and Mitsubishi Motors. Other automakers such as Ford, Mazda, and Tata Motors can be categorized into a group that shows a moderate level of supply chain complexity management efficiency.

<Figure 1: Relative efficiency of 15 DMUs, with efficiency scores from 0 to 1>



<Figure 2: Gap Analysis between Amount of Production and Efficiency Scores>

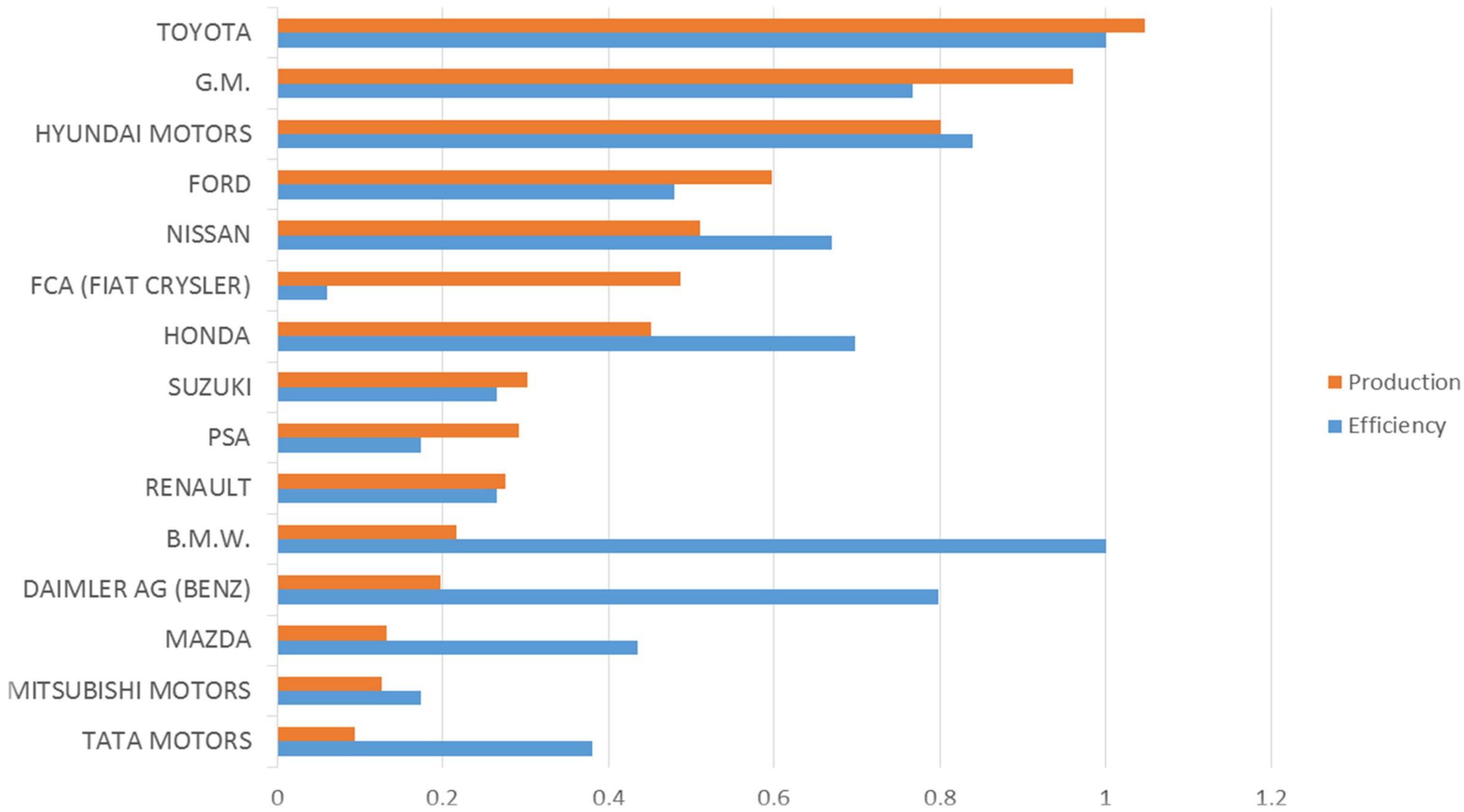


Figure 2 shows a gap between the global vehicle production and supply chain efficiency scores. First bar represents the amount of production (In 10,000,000 units) and second bar depicts the efficiency score calculated by the DEA model of this study. So, the difference between two bars shows the gap between production and supply chain complexity management efficiency. From the figure, B.M.W. is the DMU that has a high efficient score compared to its production level. In this perspective, B.M.W. could be highly evaluated than Toyota.

Lastly, Table 5 shows Excess of Input and Projection Points of each DMU. Each automaker could find a path of improvement for its own supply chain by referring the figures in the table. For example, FCA must reduce its number of product models up to 2.4, eliminating 72.6 units of its current product models, in order to make the supply chain more efficient. Likewise, practitioners of each automakers and experts in the field could acquire significant managerial insights by the projection points suggested in Table 5.

V. CONCLUSION

5.1. Managerial Implications

Supply chain complexity has been a subject which did not draw much attention from researchers until recently. However, globalized business environment makes it inevitable to focus on managing supply chain complexity in order to succeed in the market.

This paper tried to extend the model of Kim & Kim (2015) which suggest a DEA-based model to compare the relative efficiency of supply chain complexity of 12 companies in Korea. Although Kim & Kim (2015) was a significant attempt to analyze and understand supply chain complexity, its application would be limited because the study only chose Korean companies as decision making units.

In this study, input variables such as the number of product types, number of product models, and the number of production facilities were manually collected therefore validity of the dataset is guaranteed. Also, Contrary to Kim & Kim (2015), this study only focuses on global automotive industry, making it easy to understand and translate the research outcomes. Moreover, the analysis of excess of input and projection points of each decision making units could show a managerial benchmarking point for practices.

5.2. Limitations of the Study

There are some limitations of the study that should be noted despite the managerial implications above. First, the sample size of the model is too small, having only 15 decision making units with the alternative model. However, automakers with a lower ranking usually do not open their credential data to the public. The assistance of those companies is therefore needed in order to expand the boundary of this research.

Second, more relevant input variables could be considered. The number of suppliers and customers are very important to measure supply chain complexity, however, there was no way to collect those data. Bloomberg's supply chain database (SPLC) or direct assistance from the company could be possible solutions. Also, companies like Honda and Suzuki have a range of divisions other than automobile, therefore it is essential to separate group level figures from division level figures.

Third, there is a possibility of using a Negative DEA model instead of the basic CCR model used in this study. Net profit was used as a single output variable for DMUs in this study, however, it would be better to use cost data to observe the relationship between supply chain complexity and its impact on supply chain performance. Therefore, a Negative DEA model could be used to solve the cost minimization problem.

The purpose of this study was to have a better understanding the supply chain complexity and its managerial importance by using a DEA model. However, because of several limitations, this research could not identify all the relevant research questions with the subject. Therefore, future studies should be conducted to extend the boundaries of this research and to develop new research questions to deal with in-depth analysis about supply chain complexity.

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APPENDIX

< Table 3: DEA Results of the Preliminary Model with 20 DMUs>

DECISION MAKING UNITS	INPUT FACTORS					OUTPUT	EFFICIENCY SCORES	REFERENCE SETS
DMU	TYPES	DIVISIONS	BRANDS	MODELS	PLANTS	PROFITS		
(MEASURES)	(UNITS)					($ Millions)		
TOYOTA	4	8	5	63	70	18231.19	1	1
VOLKSWAGEN	2	3	12	335	119	12174.8	1	2
G.M.	4	2	11	59	50	3500	0.6605	1,2
HYUNDAI MOTORS	4	10	3	55	34	7436.807	0.7834	1,13
FORD	3	3	3	23	38	3187	0.4751	1,13
NISSAN	3	3	3	74	54	4575.74	0.6159	1,2
FCA (FIAT CRYSLER)	4	5	11	75	54	695.2	0.058	1,2
HONDA	2	9	2	160	57	5094	0.6985	1
SUZUKI	2	6	1	28	35	968.62	0.2656	1
PSA	2	4	3	39	22	995.5	0.1523	1,13
RENAULT	2	6	3	40	30	2079	0.2559	1,13
B.M.W.	1	4	4	90	30	6398.7	1	12
SAIC	4	5	4	12	7	5730	1	13
DAIMLER AG(BENZ)	2	5	10	101	55	8019	0.77	1,2,12
CHANGAN	3	2	2	22	38	1091.851	0.2341	1,2
MAZDA	2	2	1	18	21	1588	0.4355	1
DONGFENG (DFMG)	4	4	2	92	18	2094	0.3817	1,13
MITSUBISHI MOTORS	3	3	7	24	26	1182	0.1739	1,13
BAIC GROUP	4	5	1	52	27	876.15	0.2403	1
TATA MOTORS	4	6	3	116	21	2083	0.2916	1,13

<Table4: DEA Results of the Alternative Model with 15 DMUs>

DECISION MAKING UNITS	INPUT FACTORS					OUTPUT	EFFICIENCY SCORES	REFERENCE SETS
DMU	TYPES	DIVISIONS	BRANDS	MODELS	PLANTS	PROFITS		
(MEASURES)	(UNITS)					($ Millions)		
TOYOTA	*4*	*8*	*5*	*63*	*70*	*18231.19*	*1*	*1*
G.M.	*4*	*2*	*11*	*59*	*50*	*3500*	*0.7679*	*1*
HYUNDAI MOTORS	*4*	*10*	*3*	*55*	*34*	*7436.807*	*0.8398*	*1*
FORD	*3*	*3*	*3*	*23*	*38*	*3187*	*0.4788*	*1*
NISSAN	*3*	*3*	*3*	*74*	*54*	*4575.74*	*0.6693*	*1*
FCA (FIAT CRYSLER)	*4*	*5*	*11*	*75*	*54*	*695.2*	*0.061*	*1*
HONDA	*2*	*9*	*2*	*160*	*57*	*5094*	*0.6985*	*1*
SUZUKI	*2*	*6*	*1*	*28*	*35*	*968.62*	*0.2656*	*1*
PSA	*2*	*4*	*3*	*39*	*22*	*995.5*	*0.1737*	*1*
RENAULT	*2*	*6*	*3*	*40*	*30*	*2079*	*0.2661*	*1*
B.M.W.	*1*	*4*	*4*	*90*	*30*	*6398.7*	*1*	*11*
DAIMLER AG(BENZ)	*2*	*5*	*10*	*101*	*55*	*8019*	*0.799*	*1,11*
MAZDA	*2*	*2*	*1*	*18*	*21*	*1588*	*0.4355*	*1*
MITSUBISHI MOTORS	*3*	*3*	*7*	*24*	*26*	*1182*	*0.1746*	*1*
TATA MOTORS	*4*	*6*	*3*	*116*	*21*	*2083*	*0.3808*	*1*

< Table 5: Excess Quantity of Inputs and Projection Points>

DECISION MAKING UNITS	EXCESS QUANTITY OF INPUTS					PROJECTION POINTS				
DMU	TYPES	DIVISIONS	BRANDS	MODELS	PLANTS	TYPES	DIVISIONS	BRANDS	MODELS	PLANTS
	X1	X2	X3	X4	X5	X1	X2	X3	X4	X5
TOYOTA	*0*	*0*	*0*	*0*	*0*	*4*	*8*	*5*	*63*	*70*
G.M.	*3.232*	*0.464*	*10.04*	*46.904*	*36.56*	*0.768*	*1.536*	*0.96*	*12.096*	*13.44*
HYUNDAI MOTORS	*2.368*	*6.737*	*0.961*	*29.302*	*5.447*	*1.632*	*3.263*	*2.039*	*25.698*	*28.553*
FORD	*2.301*	*1.602*	*2.126*	*11.988*	*25.764*	*0.699*	*1.398*	*0.874*	*11.012*	*12.236*
NISSAN	*1.996*	*0.992*	*1.745*	*58.187*	*36.43*	*1.004*	*2.008*	*1.255*	*15.813*	*17.57*
FCA (FIAT CRYSLER)	*3.848*	*4.695*	*10.81*	*72.6*	*51.333*	*0.152*	*0.305*	*0.19*	*2.4*	*2.667*
HONDA	*0.882*	*6.765*	*0.603*	*142.398*	*37.442*	*1.118*	*2.235*	*1.397*	*17.602*	*19.558*
SUZUKI	*1.788*	*5.575*	*0.734*	*24.655*	*31.283*	*0.212*	*0.425*	*0.266*	*3.345*	*3.717*
PSA	*1.782*	*3.563*	*2.727*	*35.56*	*18.178*	*0.218*	*0.437*	*0.273*	*3.44*	*3.822*
RENAULT	*1.544*	*5.088*	*2.43*	*32.818*	*22.02*	*0.456*	*0.912*	*0.57*	*7.182*	*7.98*
B.M.W.	*0*	*0*	*0*	*0*	*0*	*1*	*4*	*4*	*90*	*30*
DAIMLER AG(BENZ)	*0.402*	*1.005*	*6.904*	*46.17*	*22.043*	*1.598*	*3.995*	*3.096*	*54.83*	*32.957*
MAZDA	*1.652*	*1.303*	*0.564*	*12.513*	*14.903*	*0.348*	*0.697*	*0.436*	*5.487*	*6.097*
MITSUBISHI MOTORS	*2.741*	*2.482*	*6.676*	*19.918*	*21.464*	*0.259*	*0.518*	*0.324*	*4.082*	*4.536*
TATA MOTORS	*3.543*	*5.086*	*2.428*	*108.799*	*12.999*	*0.457*	*0.914*	*0.572*	*7.201*	*8.001*

국 문 초 록

글로벌 자동차 제조기업의 공급망 복잡성 관리 효율성 비교

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최근 복잡성을 잘 관리하는 것에 대한 학술적, 실무적 관심이 증가하고 있다. 특히, 경영 환경이 더욱 복잡해짐에 따라 글로벌 공급망을 보유한 기업들은 이러한 복잡성 위기에 더 큰 타격을 받고 있다. 복잡성이 공급망의 성과에 부정적인 영향을 줄 것이라는 것은 자명하지만, 이러한 공급망 복잡성에 대한 학술적 연구는 그다지 많이 이루어지지 않았다.

본 연구에서는, 글로벌 자동차 산업을 대상으로 공급망 복잡성 관리 효율성을 비교하고자 시도하였다. 이를 위하여, 공급망 복잡성 관리 효율성 수준을 비교할 수 있는 CCR 기반 자료포락분석(DEA)모델이 채택되었다.

우선, 선행 문헌 연구를 통해 DEA에 사용될 투입 및 산출 변수가 선택되었다. 각 기업의 생산 모델의 수, 사업부의 수, 생산

시설의 수 등이 투입요소로, 순이익은 산출요소로 일차적으로 정리되었고 이를 통해 초기 모형이 설계되었다.

다음으로, 총 20개의 글로벌 자동차 제조기업들이 의사결정단위(DMU)로 채택되었다. 일단 초기 모형에 따라 분석을 수행한 후에, 이상치로 고려될 가능성이 있는 15개의 DMU를 제거한 후 다시 추가적인 대안 모형을 구성하여 현실 자동차 시장의 상황에 부합하는 결과를 도출하고자 하였다.

DEA 분석 결과는 아래와 같다: 효율성이 높게 관찰된 DMU들을 순서대로 나열하면 우선 Toyota와 BMW(1.0000)였으며, 다음으로는 현대자동차(0.8398)와 다임러AG(0.7990), 그리고 마지막으로 GM (0.7679)으로 정리되었다. 반면, FCA (0.061)의 효율성 점수는 가장 낮게 관측되었으며 PCA, 미쯔비시, 그리고 스즈키가 이어서 공급망 복잡성을 비효율적으로 관리하는 DMU로 판명되었다.

본 연구는 상대적 효율성 점수를 각각 비교함으로써 공급망 복잡성 개념의 이해 향상에 기여하였으며, 특히 실무자들은 투입 과다분 및 투영점 분석 결과를 바탕으로 벤치마킹을 통해 자사의 공급망 성과를 향상시킬 수 있을 것이다.

주요어: 공급망 복잡성, 자료포락분석, 글로벌 자동차 제조기업
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